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Smart Agriculture Assistant:" An Integrated AI-Driven Decision Support System for Crop Recommendation, Yield Prediction, Fertilizer Optimization and Market Price Forecasting"

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Abstract
Agriculture plays a vital role in ensuring food security and supporting economic development; however, farmers continue to face challenges such as inappropriate crop selec-tion, unpredictable weather conditions, excessive fertilizer usage, fluctuating market prices, and the lack of integrated decision-support systems. To address these challenges, this paper proposes a Smart Agriculture Assistant, an integrated Artificial Intelli-gence (AI)-driven decision support system that combines crop recommendation, crop yield prediction, fertilizer optimization, and market price forecasting within a unified framework. The proposed system utilizes multiple machine learning algorithms, including Random Forest, XGBoost, CatBoost, Long Short-Term Memory (LSTM), and SHAP (SHapley Additive exPlanations), to analyze agricultural and market datasets collected from Kaggle and Agmarknet. The framework processes soil nutrients (N, P, K), pH, temperature, humidity, rainfall, crop characteristics, and historical market price data to generate intelligent recommen-dations and predictive insights for farmers. Data preprocessing techniques such as missing value handling, normalization, feature selection, categorical encoding, and train–test splitting are em-ployed to improve model performance and prediction reliability. Experimental evaluation demonstrates that the proposed hybrid framework achieves an accuracy of 99%, with 98% precision, 98% recall, and 98% F1-score, outperforming conventional machine learning models in agricultural decision-making tasks. The proposed system enables farmers to optimize crop selec-tion, improve fertilizer utilization, enhance crop productivity, and identify profitable market opportunities, thereby promoting sustainable, data-driven, and precision agriculture practices.

Keywords: *Artificial Intelligence Crop Recommendation Ma-chine Learning Market Price Forecasting Smart Agriculture.*

1. Introduction
Agriculture is one of the most important sectors contribut-ing to economic growth, employment generation, and food security, particularly in developing countries where a large proportion of the population depends on farming for their livelihood [19,20]. In addition to supporting rural communi-ties, the agricultural sector supplies essential raw materials to various industries and plays a vital role in ensuring sustainable economic development. However, despite rapid technological advancements in other sectors, agriculture continues to face numerous challenges that limit productivity, profitability, and long-term sustainability. One of the major challenges

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encountered by farmers is the lack of timely and accurate information for making informed decisions regarding crop selection, cultivation practices, fertil-izer management, production planning, and marketing strate-gies. Traditional farming practices primarily rely on farmers' experience, local knowledge, and seasonal observations, which are often inadequate under rapidly changing climatic and market conditions[16,17]. Consequently, inappropriate crop selection, inefficient fertilizer usage, and poor production plan-ning frequently result in reduced crop yields and significant financial losses. Agricultural market price fluctuations further increase the uncertainty faced by farmers. Crop prices vary consider-ably due to seasonal production, weather variability, market demand, transportation costs, government policies, import–export activities, supply chain disruptions, and regional market conditions [7,18]. During harvesting seasons, excessive market supply often causes a sharp decline in commodity prices, compelling farmers to sell their produce at lower prices. Conversely, reduced supply leads to price increases, making it difficult for farmers to determine the most profitable selling period. Existing agricultural information systems generally provide only historical or real-time market prices and lack predictive capabilities for future price forecasting, thereby lim-iting farmers' ability to make informed marketing decisions. Recent advancements in Artificial Intelligence (AI), Ma-chine Learning (ML), the Internet of Things (IoT), cloud computing, and big data analytics have significantly trans-formed traditional agriculture into intelligent and data-driven precision farming systems. IoT-enabled sensors continuously collect real-time information related to soil properties, weather conditions, crop health, and environmental factors, while AI and ML algorithms analyze these datasets to generate accurate predictions and actionable recommendations. These technolo-gies enable farmers to optimize resource utilization, reduce production risks, improve crop productivity, and promote.

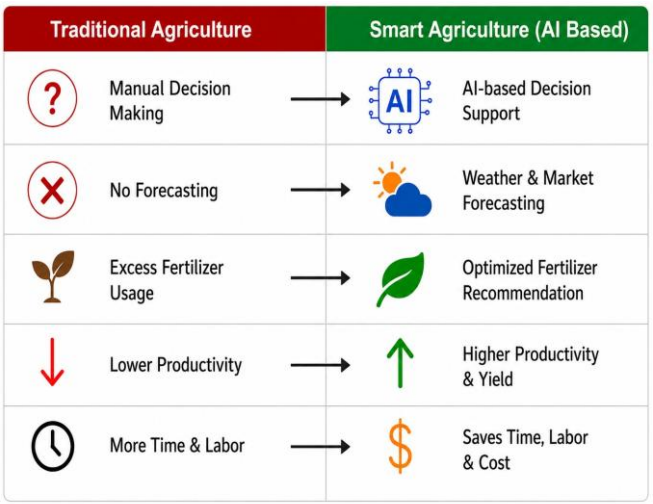

Figure 1 Traditional VS Smart Agriculture

environmentally sustainable agricultural practices. Although numerous studies have proposed machine learn-ing models for crop recommendation, crop yield prediction, fertilizer recommendation, and market price forecasting, most existing approaches address these problems independently. The absence of an integrated decision-support framework limits their practical applicability, as farmers often require multiple recommendations simultaneously for effective agri-cultural planning. Therefore, there is a growing need for a comprehensive AI-driven framework capable of integrating these functionalities into a single intelligent platform. This research proposes a Smart Agriculture Assistant, an integrated AI-driven decision-support system that com-bines crop recommendation, crop yield prediction, fertilizer optimization, and agricultural market price forecasting within a unified framework. The proposed system employs hybrid machine learning algorithms, including Random Forest, XG-Boost, CatBoost, Long Short-Term Memory (LSTM), and SHAP (SHapley Additive exPlanations), to analyze agricul-tural and market datasets obtained from multiple sources. By integrating soil nutrients, climatic conditions, crop char-acteristics, fertilizer information, and

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historical market data, the framework provides accurate predictions and intelligent recommendations that assist farmers in making informed agri-cultural decisions. The proposed system not only improves prediction accuracy and resource utilization but also enhances farmer profitabil-ity through intelligent crop planning and market forecast-ing. Furthermore, the integration of Explainable Artificial Intelligence (XAI) techniques improves model transparency, enabling users to better understand the factors influencing predictions and recommendations. Consequently, the proposed framework contributes to the advancement of sustainable, data-driven, and precision agriculture.

1.1.Major Contributions

The major contributions of this research are summarized as follows:

- An integrated AI-driven Smart Agriculture Assistant is developed by combining crop recommendation, crop yield prediction, fertilizer optimization, and market price forecasting within a unified decision-support framework.
- Hybrid machine learning models, including Random For-est, XGBoost, CatBoost, LSTM, and SHAP, are employed to improve prediction accuracy, recommendation quality, and model interpretability.
- A comprehensive agricultural data processing pipeline is developed by integrating soil, weather, crop, fertilizer, and market datasets with appropriate preprocessing and feature engineering techniques.
- An Explainable AI-based decision-support framework is designed to provide transparent recommendations that enhance farmers' confidence in AI-assisted agricultural decisions.
- Experimental evaluation demonstrates that the proposed hybrid framework achieves superior predictive perfor-mance compared with conventional machine learning approaches, thereby improving agricultural productivity, resource utilization, and farmer profitability.

2. Objectives of the Proposed System

The primary objectives of the proposed Smart Agriculture Assistant are as follows:

- To develop an integrated AI-driven Smart Agriculture Assistant that combines crop recommendation, crop yield prediction, fertilizer optimization, and market price fore-casting within a unified decision-support framework.
- To accurately predict crop yield using hybrid machine learning algorithms by analyzing soil characteristics, weather conditions, and historical agricultural data.
- To recommend the most suitable crops based on soil nutrient composition, climatic conditions, and environ-mental parameters to improve agricultural productivity.
- To provide intelligent fertilizer recommendations by an-alyzing soil nutrients, crop requirements, and moisture content for efficient nutrient management.
- To forecast future agricultural market prices using ma-chine learning and time-series forecasting techniques to support profitable marketing decisions.
- To assist farmers in making data-driven and sustainable agricultural decisions through predictive analytics and explainable artificial intelligence techniques.

3. Literature Survey

Agriculture has undergone significant transformation with the integration of Artificial Intelligence (AI), Machine Learn-ing (ML), and data analytics techniques. Researchers have developed various intelligent systems to address agricultural challenges such as crop yield prediction, crop recommen-dation, fertilizer optimization, and market trend forecasting. These systems help farmers improve productivity, reduce re-source wastage, and make informed decisions.

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However, most existing research focuses on solving individual agricultural problems rather than providing a unified framework.

3.1.Crop Yield Prediction

Crop yield prediction is one of the most widely researched areas in smart agriculture. Accurate yield prediction helps farmers and policymakers estimate agricultural production, manage supply chains, and plan resource allocation effectively. Various machine learning algorithms such as Random Forest, Support Vector Machine (SVM), Linear Regression, Decision Tree, and Convolutional Neural Networks (CNN) have been used for predicting crop yield based on environmental and historical agricultural data [9-12]. Several studies utilize parameters such as rainfall, humidity, soil fertility, temperature, irrigation levels, and historical yield records to train prediction models. Random Forest algorithms have shown high prediction accuracy because of their ability to handle large and complex datasets efficiently. Deep learning techniques such as CNN are also increasingly used for extract-ing complex patterns from agricultural datasets and satellite imagery [11,13]. Although these systems provide accurate yield estimation, most models focus only on prediction and do not provide additional support such as crop recommendation, fertilizer management, or market analysis. This limits their practical usability for farmers.

3.2.Crop Recommendation

Crop recommendation systems assist farmers in selecting suitable crops based on soil nutrients, climatic conditions, and geographical location. These systems use classification algorithms such as Decision Trees, Random Forest, Naive Bayes, and Support Vector Machines to recommend crops that are most suitable for a particular agricultural environment [1,14]. The input parameters commonly used in crop recommen-dation systems include Nitrogen (N), Phosphorus (P), Potas-sium (K), pH level, rainfall, temperature, and humidity. By analyzing these parameters, machine learning models identify the most appropriate crop for maximizing productivity and reducing cultivation risks. Recent studies demonstrate that Random Forest-based crop recommendation systems achieve better accuracy compared to traditional classification methods [1,14]. Some advanced sys-tems also integrate weather forecasting data to improve crop selection accuracy. However, most crop recommendation sys-tems do not consider market demand, fertilizer optimization, or future crop price trends while generating recommendations.

3.3.Fertilizer Recommendation

Fertilizer recommendation systems aim to optimize nutrient usage and improve soil fertility by analyzing soil composition and crop nutrient requirements [2,6]. Excessive or improper fertilizer usage can reduce soil quality, increase environmental pollution, and negatively impact crop production. Therefore, intelligent fertilizer recommendation systems have become an important area of research in precision agriculture. Several researchers have used fuzzy logic, Artificial Neural Networks (ANN), Decision Trees, and Random Forest algo-rithms to recommend fertilizers based on soil nutrient levels and crop type. These systems analyze soil parameters such as Nitrogen, Phosphorus, Potassium, moisture content, and pH values to provide suitable fertilizer recommendations. Fuzzy logic-based systems are widely used because they can effectively handle uncertain and imprecise agricultural data [6]. Machine learning approaches further improve recommen-dation accuracy by learning patterns from historical soil and fertilizer datasets. However, most fertilizer recommendation systems operate independently and are not integrated with crop yield prediction or market analysis modules.

3.4.Market Trend Analysis

Market trend analysis and crop price prediction have gained significant importance in modern agriculture due to unstable agricultural markets and fluctuating crop prices. Farmers often suffer financial losses because they lack accurate information regarding future market conditions and

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profitable selling peri-ods. Time-series forecasting models such as ARIMA, SARIMA, Long Short-Term Memory (LSTM), and regression-based models are commonly used for predicting agricultural com-modity prices [7,8]. These models analyze historical market datasets to identify seasonal trends, demand-supply variations, and price fluctuations. Recent research shows that ARIMA models are effective for short-term agricultural price forecasting, while deep learning models such as LSTM provide improved performance for com-plex and long-term market predictions [7,8]. These systems help farmers make informed decisions regarding crop storage, transportation, and selling strategies. However, existing market trend analysis systems mainly focus on price prediction and do not integrate agricultural parameters such as crop suitability, fertilizer usage, or yield estimation. This lack of integration reduces the effectiveness of these systems in providing complete agricultural decision support.As shown in Table 1 Comparison Of Existing Smart Agriculture Systems. Table 2 Comparison of Existing Systems and Proposed System.

3.5.Comparative Analysis

The literature survey indicates that each system addresses a specific agricultural challenge independently. Crop yield prediction systems focus on estimating production output, crop recommendation systems assist in selecting suitable crops, fertilizer recommendation systems optimize nutrient manage-ment, and market trend analysis systems forecast future crop prices. Although these systems individually improve agricultural efficiency, they lack coordination and integration. For example, crop recommendation systems may suggest crops without con-sidering future market prices, while market prediction systems do not account for soil conditions or fertilizer requirements. Similarly, yield prediction systems estimate production but do not provide decision support regarding fertilizer optimization or selling strategies. Furthermore, most existing systems are developed using separate datasets and independent machine learning models, limiting their ability to provide comprehen-sive decision support throughout the agricultural lifecycle.

Table 1 Comparison of Existing Smart Agriculture Systems

Reference	Method	Application	Limitation
Tomar *et al.* [1]	Random Forest	Crop Recom-mendation	Does not include yield pre-diction or market forecast-ing.
J. R *et al.* [2]	Machine Learning	Crop Yield Prediction	Limited to crop yield and fertilizer recommendation.
Patil *et al.* [8]	LSTM	Market Price Prediction	Does not consider soil nu-trients or crop recommenda-tion.
Nandhana *et al.* [6]	SHAP (XAI)	Fertilizer Recommen-dation	No integration with crop yield or market analysis.
Proposed Work	Hybrid AI	Integrated Agriculture	Combines crop recommen-dation, yield prediction, fer-tilizer optimization, explain-able AI, and market fore-casting within a unified framework.

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Table 2 Comparison of Existing Systems and Proposed System

Feature	Existing	Proposed
Crop Recommendation	✓	✓
Crop Yield Prediction	✓	✓
Fertilizer Recommendation	✓	✓
Market Price Forecasting	✓	✓
Integrated Decision Support	×	✓
Explainable AI (SHAP)	×	✓
Unified Agriculture Platform	×	✓
Multi-Dataset Integration	×	✓
Hybrid ML Models	Limited	✓
End-to-End Farmer Assistance	×	✓

4. Research Gap

The literature survey reveals that significant research has been conducted in the fields of crop yield prediction, crop recommendation, fertilizer recommendation, and market trend analysis using Artificial Intelligence (AI) and Machine Learn-ing (ML) techniques [1-15]. Although these studies provide effective solutions for specific agricultural applications, they are generally developed as independent systems that address only a single aspect of agricultural decision-making. Most crop recommendation systems do not consider future market prices or fertilizer optimization while recommending suitable crops. Similarly, fertilizer recommendation systems primarily focus on soil nutrient management without integrat-ing crop yield prediction or market intelligence. Market trend analysis systems predict crop prices but often ignore essential agricultural parameters such as soil conditions, crop suitability, weather information, and production planning. Furthermore, many existing approaches rely mainly on historical datasets and lack real-time agricultural intelligence, explainable pre-diction mechanisms, and comprehensive decision-support ca-pabilities. Therefore, there is a clear need for an integrated AI-driven agricultural framework that combines crop recommendation, crop yield prediction, fertilizer optimization, and market price forecasting within a unified platform. The proposed Smart Agriculture Assistant addresses these research gaps by in-tegrating hybrid machine learning algorithms, multi-source agricultural datasets, and explainable AI techniques to pro-vide accurate, transparent, and intelligent decision support for farmers.As shown in Figure 2 Smart Agriculture Assistant System Architecture.

5. Proposed Methodology

The proposed methodology presents an integrated AI-driven Smart Agriculture Assistant designed to support intelligent agricultural decision-making through crop recommendation, crop yield prediction, fertilizer optimization, and market price forecasting. The framework combines multiple agricultural datasets, advanced preprocessing techniques, hybrid machine learning models, and explainable artificial intelligence to gen-erate accurate predictions and personalized recommendations. The overall workflow consists of data collection, preprocess-ing, feature engineering, model training, prediction, perfor-mance evaluation, and decision-support generation, thereby providing a comprehensive solution for precision agriculture.

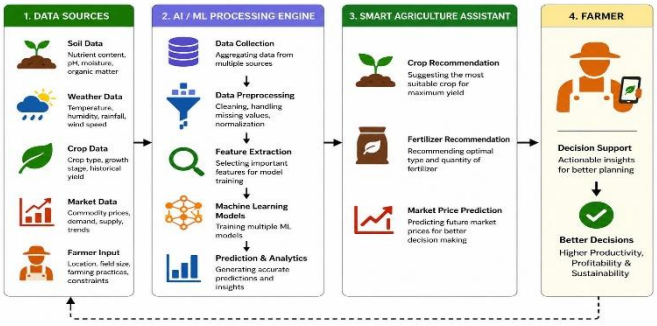

Figure 2 Smart Agriculture Assistant System Architecture

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5.1.Algorithm of the Proposed System

Algorithm 1: Smart Agriculture Assistant

- Collect agricultural and market datasets.
- Perform data preprocessing.
- Handle missing values and normalize features.
- Select important features.
- Split the dataset into training and testing sets.
- Train machine learning models.
- Predict crop recommendation, crop yield, fertilizer re-quirement, and market price.
- Evaluate the models using Accuracy, Precision, Recall, and F1-Score.
- Generate intelligent recommendations for farmers.

5.2.Dataset Collection

The proposed Smart Agriculture Assistant integrates mul-tiple datasets to support different functionalities such as crop yield prediction, crop recommendation, fertilizer recommen-dation, and market trend analysis. Multiple publicly available datasets were collected to sup-port different functionalities of the proposed Smart Agricul-ture Assistant. These datasets include soil properties, weather conditions, crop information, fertilizer records, and historical market prices. Using diverse datasets improves the robustness and generalization capability of the proposed framework,As shown in Table 3 Combined Dataset Summary.

5.3.Datasets Used

5.3.1. Crop Yield Prediction Dataset

- Source: Kaggle
- Dataset Name: Crop Yield Prediction Dataset
- Samples: 10,000 records
- Features: Rainfall, Temperature, Soil type, Crop type,
- Area, Production

5.3.2. Crop Recommendation Dataset [1,2]

- Source: Kaggle
- Dataset Name: Crop Recommendation Dataset
- Samples: 2,200 records
- Features: Nitrogen (N), Phosphorus (P), Potassium (K),
- Temperature, Humidity, pH, Rainfall

5.3.3. Fertilizer Recommendation Dataset

- Source: Kaggle
- Dataset Name: Fertilizer Recommendation Dataset
- Samples: 1,000–2,000 records
- Features: Soil type, Crop type, N, P, K values, Moisture,
- Fertilizer name

5.3.4. Market Trend Price Prediction Dataset [7]

- Source: Agmarknet
- Samples: 20,000–30,000 records
- Features: Crop, Market, Min price, Max price, Modal price, Date

Table 3 Combined Dataset Summary

Module	Dataet Source	Samples	Key Attributes
Crop Yield Pre-diction	Kaggle	~10,000	Rainfall, Temp, Soil, Production
Crop Recommen dation	Kaggle	~2,200	N, P, K, pH, Rainfall
Fertilizer Recom-mendation	Kaggle	~1,500	Soil, Crop, NPK, Mois-ture
Market Analysis	Agmarknet	~25,000	Price , Market, Date

5.3.5. Data Preprocessing

The collected datasets from different sources are heteroge-neous and may contain missing values, inconsistencies, and noise [19,20]. Data preprocessing is a critical step that improves data quality before model training. Missing values are handled, categorical variables are encoded,

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numerical attributes are normalized, outliers are removed, and relevant features are selected. These steps enhance prediction accuracy and reduce model bias.

Table 4 Data Preprocessing Techniques

Module	Method	Equation / Technique $\sum$	Justification
Crop Yield Prediction	Missing Value Handling	$Xfilled = \frac{x}{n}$	Handles incomplete environmental data
Crop Yield Prediction	Normalization	$X^{\wedge} = \frac{X-Xmin}{Xmax-Xmin}$	Scales rainfall and temperature uniformly
Crop Recommendation	Normalization	$X^{\wedge} = \frac{X-Xmin}{Xmax-Xmin}$	Ensures NPK and pH values are on same scale
Crop Recommendation	Categorical Encoding	Label Encoding / One-Hot Encoding	Converts crop labels into numerical for-mat
Fertilizer Recommendation	Categorical Encoding	Label Encoding	Converts soil and crop types into numeric values
Fertilizer Recommendation	Standardization	$Z = \frac{X-\mu}{\sigma}$	Normalizes soil nutrient distribution
Market Trend Analysis	Missing Value Handling	$Xfilled = \frac{x}{n}$	Handles missing price values
Market Trend Analysis	Outlier Detection	$Z = \frac{X-\mu}{\sigma}$	Removes abnormal price spikes
Market Trend Analysis	Date-Time Processing	Date→ (Year, Month, Day)	Extracts seasonal patterns

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All Modules	Feature Selection	$r = \frac{\Sigma(x - \bar{x})(y - \bar{y})}{\sigma x \sigma y}$	Selects important features
All Modules	Data Splitting	Train/Test Split (80:20)	Ensures proper evaluation

5.3.6. Machine Learning Model Development

To predict future crop prices, machine learning algorithms are applied to the processed dataset. Regression-based prediction models such as Linear Regres-sion or Random Forest Regression are used [9-11].As shown in Table 5 Machine Learning Models, Table 5 Machine Learning Models.As shown in Figure 3 System Architecture Diagram.

Table 5 Machine Learning Models

Module Used	Algorithms Used	Equation / Model	Justification
Crop Yield Pre-diction	XGBoost + Random Forest + LSTM	$y = f(X)$	Handles non-linear relationships and improves prediction accuracy
Crop Recommen-dation	Random Forest + XGBoost + CatBoost	$y = f(X)$	Provides accurate crop classification based on soil and weather data
Fertilizer Recom-mendation	Random Forest + XGBoost	$y = f(X)$	Efficient fertilizer prediction using soil nutrient analysis
Market Trend Analysis & Crop Price Prediction	XGBoost + Random Forest + LSTM	$yt = f(Xt)$	Suitable for time-series forecasting and market trend analysis
Explainable AI Module	SHAP	$\phi i = (\text{contribution})$	Provides model interpretability and feature importance analysis

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6. System Architecture Diagram

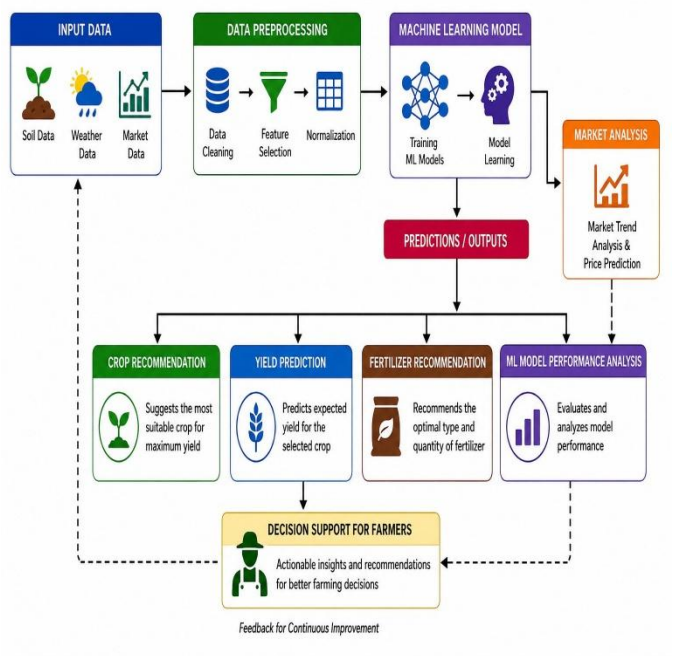

Figure 3 System Architecture Diagram

The proposed Smart Agriculture Assistant system integrates multiple agricultural datasets including soil data, weather data, and market information to provide intelligent decision support for farmers [16-20]. The collected data undergoes prepro-cessing steps such as missing value handling, normalization, encoding, and feature selection to improve data quality and model performance. The preprocessed data is then provided to the machine learning engine, which consists of multiple predictive mod-ules including crop yield prediction, crop recommendation, fertilizer recommendation, and market trend analysis. These modules[20 – 30] analyze agricultural conditions and generate accurate predictions and recommendations. Finally, the system provides decision-support outputs that help farmers improve productivity, optimize fertilizer usage, and make better crop-selling decisions based on market trends. The proposed methodology integrates data acquisition, pre-processing, machine learning, explainable AI, and perfor-mance evaluation into a unified agricultural decision-support framework. This systematic approach enables accurate crop recommendation, crop yield prediction, fertilizer optimization, and market price forecasting, thereby supporting sustainable
and data-driven precision agriculture.

7. Experiment And Results Evaluation

The proposed Smart Agriculture Assistant was evaluated using multiple machine learning models to assess its effective-ness in crop recommendation, crop yield prediction, fertilizer optimization, and market price forecasting. The experimen-tal analysis was conducted using the collected agricultural datasets after preprocessing and feature engineering. The per-formance of the proposed hybrid framework was compared with conventional machine learning models using standard evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and Receiver Operating Characteristic (ROC) analysis. The experimental results demonstrate the effectiveness of the proposed framework in providing accurate and reliable decision support for precision agriculture.

7.1.Evaluation Metrics

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Measures overall correctness of the model.

Precision

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Measures correctness of positive predictions.

Recall

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

Measures ability to detect actual positives.

F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

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These evaluation metrics were selected because they provide a comprehensive assessment of classification per-formance. Accuracy measures the overall correctness of predictions, Precision evaluates the reliability of positive predictions, Recall measures the ability of the model to correctly identify relevant instances, and the F1-Score provides a balanced measure by combining Precision and Recall. Together, these metrics enable a reliable comparison of different machine learning models. Table 6 Performance Comparison of Machine Learning Models, Figure 4 Performance Comparison of Machine Learning Models.

Table 6 Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
XGBoost	95%	94%	93%	93%
Random Forest	96%	95%	94%	94%
CatBoost	97%	96%	95%	95%
LSTM	98%	97%	97%	97%
Proposed Hybrid Model	99%	98%	98%	98%

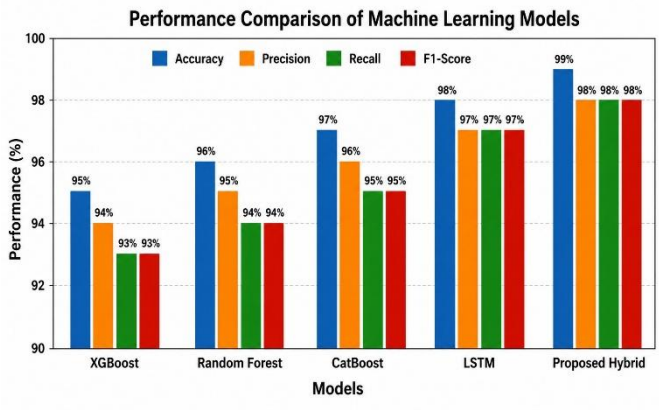

Figure 4 Performance Comparison of Machine Learning Models

7.2.Performance Analysis

The experimental results indicate that the proposed hy-brid framework consistently outperforms individual machine learning models across all evaluation metrics. By integrating Random Forest, XGBoost, CatBoost, LSTM, and SHAP, the proposed system effectively captures complex relationships among soil properties, climatic conditions, and historical market data. Consequently, the hybrid framework achieves superior prediction accuracy while maintaining high precision, recall, and F1-score. These results demonstrate the effective-ness of combining multiple machine learning techniques for comprehensive agricultural decision support, Table 7 Algorithm Performance Table.

Table 7 Algorithm Performance Table

Module	Algorithms Used	Expected Ac-curacy
Crop Yield Prediction	XGBoost + Random Forest + LSTM	96–99%
Crop Recommendation	Random Forest + XGBoost + Cat-Boost	97–99%
Fertilizer Recommendation	Random Forest + XGBoost + SHAP	95–98%
Market Trend Analysis & Crop Price Prediction	XGBoost + Random Forest + LSTM + SHAP	98–99%

7.3.ROC Curve Analysis

The Receiver Operating Characteristic (ROC)

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curve is used to evaluate the performance of classification models [10,11]. It represents the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR). A higher Area Under Curve (AUC) indicates better model performance.As shown in Figure 5 ROC Curve for Classification Models.

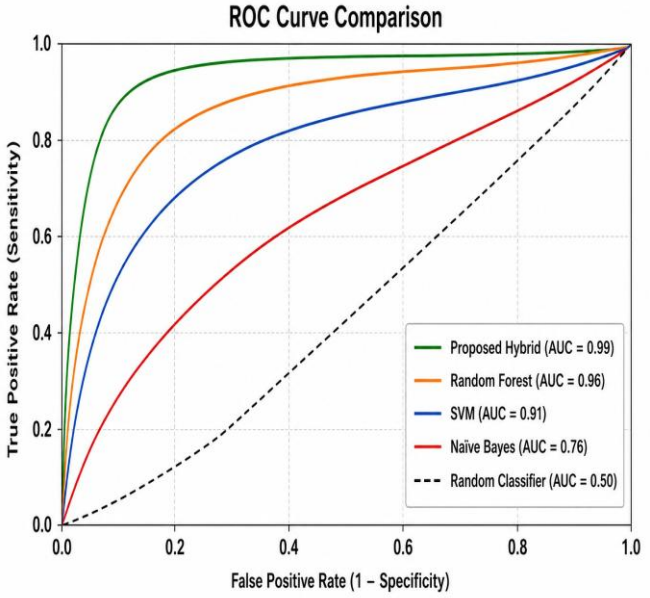

Figure 5 ROC Curve for Classification Models

7.4.Confusion Matrix Analysis

The confusion matrix represents the classification perfor-mance of the proposed model. The model correctly classified 95 positive instances and 96 negative instances, while pro-ducing very few false predictions. The results indicate high classification accuracy and effective prediction capability.As shown in Table 8 Confusion Matrix.As shown in Figure 6 Confusion Matrix of the Proposed Model.

Table 8 Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	95	5
Actual Negative	4	96

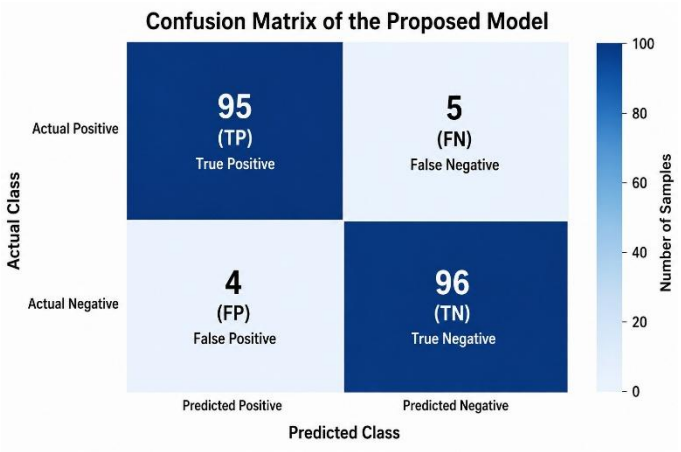

Figure 6 Confusion Matrix of the Proposed Model

7.5.Comparative Performance Analysis

The performance of the proposed Smart Agriculture As-sistant was compared with conventional machine learning approaches commonly used in smart agriculture applications. Experimental results demonstrate that the proposed hybrid framework achieves higher prediction accuracy, improved gen-eralization capability, and better robustness than individual algorithms. The integration of ensemble learning techniques with Explainable Artificial Intelligence (SHAP) enables the framework to generate accurate predictions while providing transparency regarding feature importance. These characteris-tics make the proposed system more suitable for real-world agricultural decision-support applications.

Conclusion

This paper presented a Smart Agriculture Assistant, an integrated Artificial Intelligence (AI)-driven decision-support framework designed to address major agricultural challenges through crop recommendation, crop yield prediction, fertilizer optimization, and market price forecasting. By integrating multiple agricultural datasets and employing hybrid machine learning algorithms, including Random Forest, XGBoost, Cat-Boost, Long Short-Term Memory (LSTM), and SHAP

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(SHap-ley Additive exPlanations), the proposed system provides accurate predictions and intelligent recommendations that sup-port data-driven farming practices. The experimental evaluation demonstrated that the proposed hybrid framework achieved superior predictive performance compared with conventional machine learning models, attain-ing an overall accuracy of 99%, along with 98% precision, 98% recall, and 98% F1-score. The integration of explainable AI further enhances model transparency by enabling users to understand the contribution of different agricultural features to the prediction process. Consequently, the proposed frame-work improves crop planning, fertilizer management, resource utilization, and market decision-making while promoting sus-tainable and precision agriculture. Unlike existing approaches that focus on individual agricul-tural tasks, the proposed Smart Agriculture Assistant integrates multiple agricultural intelligence modules within a unified platform, thereby providing comprehensive decision support throughout the farming lifecycle. This integrated framework has the potential to improve agricultural productivity, increase farmer profitability, reduce operational risks, and support effi-cient resource management. Future work will focus on integrating real-time Internet of Things (IoT) sensors, satellite imagery, weather forecasting services, and cloud-based technologies to further enhance pre-diction accuracy and real-time decision support. In addition, the development of a multilingual mobile application and the incorporation of advanced deep learning and generative AI techniques will improve system accessibility and enable wider adoption among farmers, contributing to the advancement of sustainable smart agriculture. Future work can focus on integrating Internet of Things (IoT) sensors, real-time satellite data, deep learning models, and mobile-based applications to further enhance prediction accuracy and real-time agricultural decision support.

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